Improving Heading Accuracy in Smartphone-based PDR Systems using Multi-Pedestrian Sensor Fusion

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***Abstract*—Accurately estimating the heading of each step is critical for pedestrian dead reckoning (PDR) systems, which use step length and step heading to continuously update the current location based on a previous known location. While magnetometer is a key source of heading information, poor accuracy of consumer grade hardware coupled with frequent presence of manmade magnetic disturbances makes accurate heading estimation a challenging problem in smartphone-based PDR systems. In this paper we propose the concept of multi-pedestrian sensor fusion where sensor data from multiple pedestrians walking in the same direction are fused to improve the heading accuracy. We have conducted experiments with 3 subjects walking together in the corridors of 4 different buildings. Based on the magnetometer data collected from these subjects, we find that multi-pedestrian fusion has the potential to improve magnetometer-based heading error by 42% compared to the case when no fusion is used. We further show that a very basic fusion algorithm that simply takes the average of 3 individual heading estimations can yield a 27.77% error reduction.**

***Index Terms*—Heading Estimation, Pedestrian Dead Reckoning, Multi-Sensor Data Fusion, Indoor Localization.**

I. Introduction

PDR, which uses step length and heading estimation to compute current location relative to a previously known location, is a viable positioning alternative to GPS in indoor environments. While magnetometer is considered as a key source of heading information for PDR, it is known to exhibit large errors when used indoors due to presence of significant magnetic disturbances caused by metallic infrastructure. Because these perturbations are likely to be highly localised, in this paper, we propose the concept of multi-pedestrian sensor fusion where sensor data from multiple pedestrians walking in the same direction are fused to improve the heading accuracy. The key hypothesis is that pedestrians experiencing high perturbation will benefit from those experiencing no or minor perturbations if their devices could share their sensor data in real-time. Emerging device-to-device communication standards, such as WiFi-Direct[1], are definitely opening up such data sharing possibilities.

To test this hypothesis, we collected magnetometer readings from three pedestrians walking in the same direction in the corridors of 4 different buildings. Our study reveals the following interesting results:

- When pedestrians use their individual heading estimations, i.e., when no fusion is used, the average heading error from the true heading is 12.45 degrees.
- A simple averaging of all three individual estimations, which is called Naïve fusion in this paper, reduces the error to 8.99 degrees, which yields an improvement of 27.77%.
- If, however, we were able to filter out the highly perturbed data, which is called Oracle fusion in this paper, we could potentially reduce the error to 7.21 degrees or achieve up to 42% error reduction.

The rest of our paper is organized as follows. In the next section, we describe the data collection methodology followed by the multi-pedestrian fusion analysis in Section III. Related work is reviewed in Section IV before concluding the paper in Section V.

II. Data collection

We performed multiple experiments to collect the data for our study. In order to ensure diversity in environment conditions (especially magnetic perturbation), experiments were conducted in 4 different building on our university (UNSW) campus. In each building, we chose different corridors to provide different heading directions.

Each experiment consisted of three subjects carrying an android smartphone. The subjects held the smartphone horizontally in their hand and walked along the corridor of the building. They ensured that they walked *parallel* to the corridor of the building, thus having the same heading, by following the line between the floor tiles. The smartphones record the magnetometer readings at 16Hz. Table I shows the building name and true heading used in each experiment. The true headings are estimated by assuming that the corridor is parallel to the face of the building.

The three subjects walked in a line parallel to the corridor, one after another, with a gap of 5 meters between them. This means that, at a given time, the three subjects were always at different locations. The motivation for doing this is to test whether the magnetic perturbation at different places are independent. We identify the three subjects as “Back”, “Middle” and “Front”.

After obtaining the magnetometer readings, we use the two horizontal components m_x and m_y to compute the estimated

[1]http://www.wi-fi.org/discover-and-learn/wi-fi-direct

TABLE I
INDOOR LOCATIONS FOR DATA COLLECTION, UNSW, SYDNEY

Buildings	True heading
Library, 3rd Floor	188.99
	9.35
Electrical Engineering Building, 2nd Floor	278.99
	98.9
Robert Webster Building, LG Floor	99.27
	279.18
Old Main Building, Ground Floor	279.24
	99.46

heading with respect to the magnetic North from

$$h = tan^{-1}(\frac{m_x}{m_y}) \tag{1}$$

We will use these heading estimations for multi-pedestrian data fusion in the next section.

III. MULTI-PEDESTRIAN DATA FUSION

In order to motivate multi-pedestrian data fusion, we plot the estimated headings from the three subjects in Figure 1 for an experiment conducted in the Library building. The figure also shows the true heading which is 188.99 degrees. The figure shows that the estimated headings deviate from the true heading due to man-made magnetic perturbation. Note also that, at a given time, each magnetometer experienced a different amount of perturbation. Consider the time interval between 11.44 to 13.64 seconds, bounded by the two vertical bars in Figure 1. In this interval, the Front subject experienced a large perturbation in heading estimation while both the Middle and Back subjects did not. If there was a method to tell that the Front heading estimation was erroneous, then we could discard it and replace it by the average of the other two heading estimates to obtain better heading estimation. This is the key idea behind Oracle fusion. In this section, we will compare the performance of two different fusion strategies. We first describe the fusion strategies.

A. Fusion methods

We define two different fusion methods, Naïve and Oracle. We assume that all the subjects exchange their estimated heading using wireless communication such as WiFi. We assume there are n subjects. At a given sampling time, subject i calculates its heading estimates h_i. After the exchange of heading estimates, each subject has the data: h_1, h_2, ..., h_n. The method is applied for each sampling time.

For Naïve fusion, each subject computes the simple average $\frac{1}{n}\sum_{i=1}^{n} h_n$ of all estimated headings. Note that Naïve fusion works well if the estimated headings are perturbed by random zero-mean noise but its performance under other types of perturbations can be poor.

The Oracle method is used here to quantify the best possible improvement provided by data fusion. The method assumes that each subject knows the true heading h_T and uses a given threshold γ. It also assumes each subject has all the estimated headings from all subjects: $\mathcal{H} = \{h_1, ..., h_n\}$. Each subject eliminates all the estimated headings in $\mathcal{H}$ that exceed an error threshold γ from the true heading h_T, or in other words, each subject determines the set $\tilde{\mathcal{H}} = \{h_i \in \mathcal{H} : h_i \in [h_T - \gamma, h_T + \gamma]\}$. If the set $\tilde{\mathcal{H}}$ is non-empty, then the Oracle method returns the simple average of the heading estimates in $\tilde{\mathcal{H}}$. Otherwise, if $\tilde{\mathcal{H}}$ is empty, the Oracle method uses the subject's own heading estimate, i.e. subject i uses h_i.

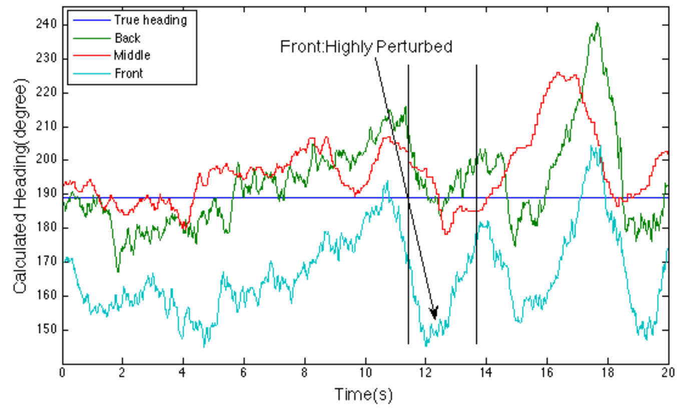

Fig. 1. Library, 3rd Floor, True heading=188.99

TABLE II
LIBRARY, 3RD FLOOR, TRUE HEADING=188.99,NAÏVE

Participant	Average error (No Fusion)	Naïve Fusion error
Front	23.34	8.91
Middle	9.35	
Back	10.48	
Average	14.42	8.91

B. Results and discussions

For each building, we have collected multiple sets of data at different times of the day where each data set contains approximately 900 magnetometer samples for each subject. For a given data set, we applied the two fusion methods to each sample to obtain the fused headings. The heading error is calculated as the absolute difference between the true and the estimated headings. For each data set, we obtain one heading error data by averaging the 900 error data computed for the 900 samples.

Table II shows the results of applying Naïve fusion to one of the experiments conducted on the third floor of the Library building. It compares Naïve fusion against the average heading error of each subject when no data fusion is used. The last row of the table shows the results of averaging over all subjects. Note that the results of Naïve fusion is independent of the subject. It can be seen that Naïve fusion reduces the average error from 14.42 degrees to 8.91 degrees.

Table III shows the results of applying Oracle fusion to the same dataset. The different γ values used are shown in the first column. In columns 2–4, we show the average heading

TABLE III
LIBRARY, 3RD FLOOR, TRUE HEADING=188.99,ORACLE

γ	Oracle (Perfect fusion)					
	Average error Back	Average error Middle	Average error Front	1 above γ	2 above γ	3 above γ
1	9.55	8.71	19.97	4	133	843
10	5.67	5.69	5.17	499	385	91
12	5.39	5.42	5.07	625	287	53
15	4.80	4.78	4.74	699	189	7
20	4.56	4.56	4.56	675	82	0
25	4.72	4.72	4.72	562	42	0
30	5.75	5.75	5.75	408	4	0
35	6.78	6.78	6.78	221	0	0
40	8.24	8.24	8.24	62	0	0
45	8.70	8.70	8.70	19	0	0
50	8.85	8.85	8.85	5	0	0
60	8.90	8.90	8.90	0	0	0
70	8.90	8.90	8.90	0	0	0
80	8.90	8.90	8.90	0	0	0
90	8.90	8.90	8.90	0	0	0
100	8.90	8.90	8.90	0	0	0
120	8.90	8.90	8.90	0	0	0
140	8.90	8.90	8.90	0	0	0
150	8.90	8.90	8.90	0	0	0

error for each subject for different values of γ. Note that each subject can have a different average error because if all the heading estimates at a given time exceed the threshold γ, each subject uses its own heading estimate as the output of the Oracle method. In column 5, we show for each value of γ, the number of sampling times where exactly 1 of the estimated headings is above the threshold γ, or equivalently, the number of sampling times that the set $\tilde{\mathcal{H}}$ has exactly 2 elements. Columns 6 and 7 are similarly defined. For $\gamma = 1$, we find that, for a lot of sampling times, all the three heading estimates have an error greater than γ. This is due to low value of error threshold γ. As the threshold γ increases, the number of sampling times that all three heading estimates are above the threshold become lower.

An interesting observation that can be made from columns 2–4 in Table III is that, as γ increases, the average heading error for each subject decreases and then increases again. This means that there is an optimal threshold γ that gives the minimum estimation error. This observation is also found in the data from the other experiments. In Figure 2, we plot the average heading error for each subject against the γ for an experiment conducted in the Robert Webster Building.

In Table IV, we compare the fusion methods over all the 10 data sets from the four buildings. Four different methods are used: no fusion, Naïve fusion, Oracle fusion with a fixed threshold of 10 and Oracle fusion with the optimum threshold that gives the minimum heading error. Percentage improvements, compared to the case when no data fusion is used, are shown in brackets. The last row shows the average error and percentage improvements over all the 10 experiments.

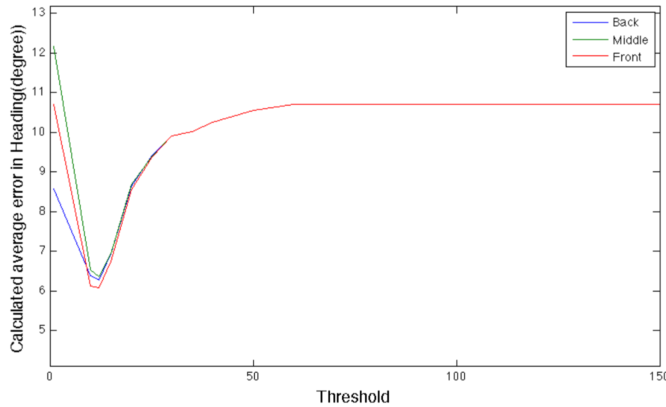

Fig. 2. Heading error for Oracle fusion in Robert Webster Building, LG Floor, True heading=99.27.

It can be seen from Table IV that Naïve fusion is useful and can deliver improvement of 27.77% on average. For Oracle fusion with a fixed threshold γ, the improvement is -24.77%. This means a fixed γ does not deliver good results. Finally, the Oracle fusion with optimum threshold delivers the best improvement of 42.04%.

IV. RELATED WORK

Some approaches are currently in use to improve heading estimation such as sensor fusion by Kalman Filter [1]–[3], magnetometer fingerprinting [4]–[7], and magnetometer filtering [8]–[10]. Kalman filter is a sophisticated filter and uses magnetometer, accelerometer and gyroscope to estimate pedestrian's heading. In magnetometer fingerprinting, different algorithms are used to match the observed magnetometer reading with a pre-surveyed database. In magnetometer filtering, the perturbed data are filtered to improve its accuracy. Our proposed fusion algorithms rely only on smartphone's magnetometer without using any infrastructure.

V. CONCLUSION

While magnetometer is considered as a key source of heading information for PDR, it is known to exhibit large errors when used indoors due to presence of significant magnetic disturbances caused by metallic infrastructure. Since these perturbations are highly localised, it may be possible that not all pedestrians are affected (equally) at the same time, opening up the possibility of reducing error by fusing sensing data among multiple pedestrians walking in the same direction. In this paper, we have experimentally quantified the error reduction potential of such multi-pedestrian sensor fusion. Our study reveals that there is opportunity for significant error reduction (42.04%), but only 27.77% is achievable with a Naïve averaging. This calls for research in more advanced fusion models to achieve the full potential of multi-pedestrian sensor fusion.

TABLE IV
COMPARISON OF THE FUSION ALGORITHMS OVER 10 DATA SETS FROM FOUR BUILDINGS

Building, Day, (True Heading)	No-fusion	Naïve fusion(%)	Oracle fusion, γ=10(%)	Oracle fusion, Optimum γ(%)
Library, Day 1, (188.99)	14.42	8.91(38.21)	5.51(61.77)	4.64(67.82)
Library, Day 2, (188.99)	21.20	12.01(43.37)	14.56(31.35)	10(52.84)
Library, Day 1, (9.34)	17.94	15.92(11.28)	55.85(-211)	14.56(18.86)
Library, Day 2, (9.34)	12.18	4.92(59.60)	39.53(-224)	5.97(50.98)
Electrical Engineering Building, Day 1, (278.99)	11.61	11.08(4.52)	8.80(24.16)	8.32(28.31)
Electrical Engineering Building, Day 2, (98.9)	9.75	5.77(40.82)	5.26(46.01)	5(48.71)
Robert Webster Building, Day 1, (99.27)	9.61	8.72(9.25)	7.20(25.07)	6.7(30.31)
Robert Webster Building, Day 2, (279.18)	11.75	10.70(8.96)	6.35(45.96)	6.24(46.88)
Old Main Building, Day 1, (279.24)	6.60	5.69(13.75)	4.54(31.29)	4.53(31.39)
Old Main Building, Day 2, (99.26)	9.36	6.18(34.24)	7.68(18.24)	6.18(34.24)
Average	**12.45**	**8.99(27.77)**	**15.53(-24.77)**	**7.21(42.04)**

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